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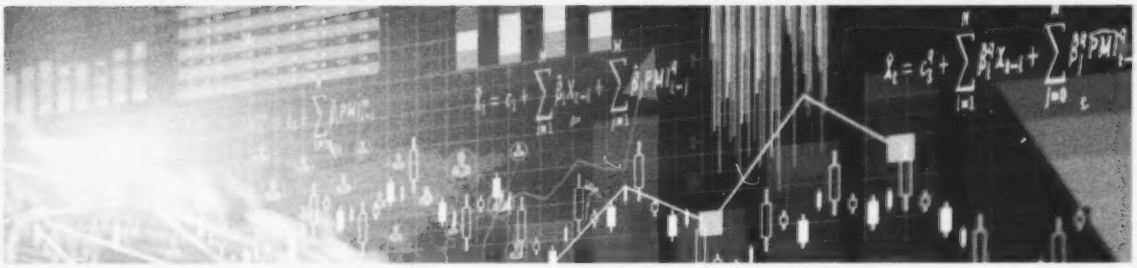
Price Selection



by Carlos Carvalho and Oleksiy Kryvtsov

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by

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Abstract

We propose a simple, model-free way to measure price selection and its impact on inflation. Price selection exists when prices that change in response to aggregate shocks are not representative of the overall population of prices. Due to selection, increases (decreases) in inflation can be amplified because adjusting prices tend to originate from levels far below (above) the average. Using detailed micro-level consumer price data for the United Kingdom, the United States and Canada, we find robust evidence of strong price selection across goods and services. At a disaggregate level, price selection accounts for around 36% of inflation variance in the United Kingdom and the United States, and 28% in Canada. Price selection is stronger for goods with less frequent price changes or with larger average price changes. Aggregation largely washes out price selection for regular price changes, but not for changes associated with price discounts. This evidence favors multi-sector sticky-price models with strong price selection at a sector level.

Bank topics: Fluctuations and cycles; Inflation and prices; Transmission of monetary policy
JEL codes: E31, E51

Résumé

Dans cette étude, nous proposons un moyen simple, qui ne recourt à aucun modèle, de mesurer la sélection des prix et les effets que cette dernière peut avoir sur l'inflation. Il y a sélection des prix lorsque les prix qui changent en réaction à des chocs globaux ne sont pas représentatifs de l'ensemble des prix. La sélection peut amplifier la hausse (ou la baisse) de l'inflation puisque les prix qui s'ajustent étaient au départ très inférieurs (ou très supérieurs) à la moyenne. L'analyse de données microéconomiques détaillées sur les prix à la consommation au Royaume-Uni, aux États-Unis et au Canada, montre de façon concluante une forte sélection des prix pour les biens et les services. À un niveau désagrégé, la sélection des prix représente environ 36 % de la variance de l'inflation au Royaume-Uni et aux États-Unis, et 28 % au Canada. La sélection des prix est plus forte dans le cas des biens ayant des variations de prix moins fréquentes ou en moyenne plus prononcées. L'agrégation élimine en grande partie la sélection des prix pour ce qui est des variations des prix réguliers, mais pas des prix réduits. Ces observations plaident pour les modèles multisectoriels à prix rigides avec une forte sélection des prix au niveau sectoriel.

Sujets : Cycles et fluctuations économiques; Inflation et prix; Transmission de la politique monétaire
Codes JEL : E31, E51

Non-technical summary

Price selection is associated with the dynamics of the distribution of price adjustments across firms and products; it works in the direction of amplifying the inflation response. There is hardly any direct evidence for whether price selection is empirically important. In this paper, we provide such evidence and explain its implications for sticky price models.

We propose a simple, model-free way to measure price selection and its impact on inflation. Price selection exists when prices that change in response to macroeconomic or monetary disturbances are not representative of the overall population of prices. Due to selection, increases (decreases) in inflation can be amplified because adjusting prices tend to originate from levels far below (above) the average.

Using detailed micro-level consumer price data for the United Kingdom, the United States and Canada, we find robust evidence of strong price selection across goods and services. At a disaggregate level, price selection accounts for around 36% of inflation variance in the United Kingdom and the United States and 28% in Canada. Price selection is stronger for goods with less frequent price changes or with larger average price changes. Aggregation largely washes out price selection for regular price changes, but not for changes associated with price discounts.

Standard multisector models can account for approximately 60% of price selection across sectors and can explain only a modest portion of the aggregation effect. Models that exploit additional dimensions of heterogeneity across goods and retailers should have a better chance of accounting for empirical evidence. Adding information frictions or an interaction of large sector-specific shocks and non-linearities in these models should increase the level and range of price selection at a sector level, while leaving aggregate selection relatively weak.

In all, by offering a direct measure of price selection in the data, our paper helps to better calibrate the features of business cycle models that help them match inflation dynamics and more accurately identify the determinants of monetary non-neutrality. Standard models have predominantly relied on Calvo nominal price adjustment and real rigidities to account for business cycles and the flat Phillips curve. Our results suggest that a significant share of inflation volatility may be unaccounted for by these models, leading them to predict a flatter Phillips curve.

1 Introduction

The extent to which prices respond to new information—to macroeconomic shocks, in particular—is a fundamental question in economics. In macroeconomic data, the correlation between inflation and economic slack is fairly low, suggesting that prices are relatively insensitive to economy-wide disturbances. This muted sensitivity is usually associated with the idea of a "flat" Phillips curve. Much of the literature has concentrated on reconciling the flat Phillips curve with evidence of ample price flexibility at the microeconomic level. This usually requires mechanisms that create a large "price contract multiplier," whereby individual prices respond only gradually to some aggregate shocks due to market frictions that affect the allocation of goods or production factors or due to information frictions.[1] This literature, however, has devoted less attention to *price selection*—the mechanism that is associated with the dynamics of the distribution of price adjustments across firms and products and that works in the direction of amplifying the sensitivity of inflation to economic slack and its response to aggregate shocks. The goal of this paper is to study price selection and its impact on inflation dynamics.

In general terms, selection exists whenever prices that change in response to a shock are not representative of the pre-shock price distribution. The key for understanding inflation dynamics is whether selection has first-order effects on the response of inflation—i.e., whether prices that do change in response to a shock amplify or dampen the aggregate inflation response. For example, if, in response to an unanticipated monetary expansion, price increases come from below-average levels, they would tend to be larger than an average price change. If so, the inflation response would be greater, and the associated real effects of the monetary expansion smaller. Alternatively, smaller price increases that originated from above-average levels would mute the aggregate inflation response and hence increase the real effects of the expansionary shock. All in all, price selection is a key determinant of the sensitivity of inflation to shocks and of the degree of monetary non-neutrality.

While the possibility of price selection is a prominent theoretical insight, there is hardly any direct evidence whether it is empirically important. In this paper, we propose a simple model-free way of measuring price selection using micro price data and assess its impact on inflation.

Our measure of price selection is based on the idea outlined above. For the subset of prices that change between periods $t-1$ and t, we compute their average level at $t-1$ relative to the average level of *all* prices in the population at $t-1$. We call this average price-relative the "preset price" or "preset price-relative." If preset price movements covary with inflation, there is price selection. For example, negative comovement implies that upward (downward) movements in inflation are largely driven by prices that adjust from below-(above-)average levels, and it is therefore associated with higher sensitivity of inflation to disturbances. We measure this comovement using micro price data.

We employ three detailed micro price datasets to measure price selection. For the United Kingdom, we use the dataset underlying construction of the consumer prices index (CPI) by the U.K.

[1] Important contributions to this voluminous literature include Chari, Kehoe, and McGrattan (2000), Christiano, Eichenbaum, and Evans (2005), and Smets and Wouters (2007). Klenow and Malin (2010) and Nakamura and Steinsson (2013) provide a review of empirical evidence produced by this literature.

Office for National Statistics (ONS). The dataset provides unit prices for goods and services that are included in the consumption expenditure component of the U.K. National Accounts, representing about 57% of the U.K. CPI basket. Prices are collected locally for more than 1,100 categories of goods and services a month and more than 14,000 retail outlets across the United Kingdom. The sample period includes 236 months, from February 1996 to September 2015. Likewise, for Canada we employ the Consumer Price Research Database (CPRD), compiled by Statistics Canada from price surveys used to construct the non-shelter portion of the Canadian CPI. The dataset contains information about prices posted by retail outlets across Canada during 143 months from February 1998 to December 2009, spanning more than 700 categories of goods and services representing about 61% of the consumption basket underlying the CPI. Finally, for the United States, the Symphony IRI scanner dataset provides weekly expenditures and quantities for individual products across 31 product categories over 132 months from January 2001 to December 2011. The product categories cover food and personal care goods sold by grocery stores in 50 U.S. metropolitan areas.

We first compute the average price change and preset price-relative for each month, product category, and sampling stratum (given by location and store type). This level of disaggregation accords with sample design for collecting prices and constructing the CPI in the United Kingdom, the United States, and Canada (ILO, 2004). We measure the extent of price selection at the stratum level by the coefficient of a regression of the preset price-relative on the average size of price changes. The absolute value of this coefficient is equal to the share of the variance of the average size of price changes explained by the preset price, thus providing a convenient metric for gauging the economic significance of price selection. By construction, zero price selection means that changes in the preset price are uncorrelated with inflation fluctuations.

In exploring micro data to perform a variance decomposition of inflation, our paper is related to Klenow and Kryvtsov (2008), who decompose inflation into components due extensive and intensive margins of price adjustment. Our paper is also related to Bils, Klenow, and Malin (2012), who use microdata to construct what they call a "reset price inflation" measure, which they employ to assess sticky-price models. Their measure relies on observations of individual reset prices of adjusters, which are then used to impute unobserved reset prices for non-adjusters. We provide complementary results by exploiting price selection, which only relies on (observed) preset prices of adjusters.

For our baseline case, we exclude price changes associated with price discounts and product substitutions and control for stratum and calendar-month fixed effects. The weighted mean price selection across strata is −0.371 for the United Kingdom, −0.360 for the United States, and −0.285 for Canada, all highly statistically significant, and it is robust to different empirical specifications. Including price changes associated with price discounts or substitutions does not materially influence price selection at a stratum level.

By exploiting rich variation in price adjustment across product strata, we document that price selection is stronger for strata where prices change less frequently: a 10 percentage point decrease in the frequency of price changes is associated with an additional 1.9 to 6.7 percentage points of

inflation variance explained by preset prices. Furthermore, we find that price selection is stronger in strata with a larger size of price changes: a 5 percentage point increase in the average size of price changes is associated with an additional 1.5 to 2.5 percentage points of inflation variance explained by preset prices. In contrast, we do not find a robust relationship between price selection and the standard deviation of price spell durations or the kurtosis of price changes—two moments that underlie sufficient statistics derived by Carvalho and Schwartzman (2015) and Alvarez, Le Bihan, and Lippi (2016), that are theoretically linked to selection effects and monetary non-neutrality in standard sticky-price models.

Finally, we measure the degree of price selection at the *aggregate* level. We find that regular-price selection is substantially weakened. For the baseline case—no discounts or substitutions—price selection is −0.197 for the United Kingdom, and it is not significantly different from zero for the United States and Canada. Similar to the stratum-level evidence, including substitutions does not change price selection at the aggregate level. By contrast, including price discounts restores a substantial degree of price selection in the United Kingdom (−0.394) and meaningful price selection in the United States (−0.140). Hence, aggregation largely washes out price selection for regular price changes, but not for price discounts. This finding reflects a special nature of price discounts as an additional margin of price flexibility and underscores their role for amplifying cyclical variation of the aggregate price level, recently emphasized for the United Kingdom and United States by Kryvtsov and Vincent (2017). In Canada, aggregate price selection is close to zero for either regular or all posted prices, consistent with less cyclicality in price discounts and coarser strata in the Canadian sample.

In the second part of the paper, we study the implications of our empirical evidence for business cycle models with pricing frictions. The sticky-price literature has emphasized so-called "selection effects" as a key determinant of the inflation-output trade-off. Selection effects tend to increase the sensitivity of aggregate inflation to economic slack for a given degree of microeconomic price stickiness, and hence they often lead to smaller monetary non-neutralities (e.g., Caballero and Engel, 2007). Caplin and Spulber (1987), Danziger (1999) and Golosov and Lucas (2007) emphasize selection effects in menu-cost models, where firms can choose to incur a menu cost to change their prices. Selection effects also arise in models with time-dependent price adjustment, where after a shock some prices are expected to take longer to adjust than others (Carvalho and Schwartzman, 2015). Under specific assumptions, some models yield sufficient statistics for selection that can be computed from moments estimated from price micro data (Carvalho and Schwartzman, 2015; Alvarez, Le Bihan, and Lippi, 2016). The degree of selection can also be estimated indirectly from applied theoretical models matched to observed micro price behavior. Examples in the literature show that the degree of selection may be affected by factors such as product-level disturbances (Gertler and Leahy, 2008), economies of scale in price-adjustment technology (Midrigan, 2011), the size of aggregate shocks (Alvarez, Lippi, and Passadore, 2017), stochastic volatility of idiosyncratic shocks (Karadi and Reiff, 2014), the number of products per retailer (Bhattarai and Schoenle, 2014; Alvarez and Lippi, 2014), the risk of pricing mistakes (Costain and Nakov, 2011b), the slope of the

hazard rate of price adjustment (Carvalho and Schwartzman, 2015), and sectoral heterogeneity in price stickiness (Carvalho, 2006; and Nakamura and Steinsson, 2010).[2] The most widely used Calvo (1983) sticky-price model with random and exogenous timing of price adjustments represents an extreme case with no selection effects. In sum, sticky-price models predict a wide range for the size of selection effects and the associated monetary non-neutrality.

Our measure of price selection is model free and does not rely on any of the aforementioned model features that are material for selection effects in sticky-price models. Nevertheless, we show that it accurately captures the macroeconomic implications of selection effects in these models. We do so by computing our measure of price selection in standard sticky-price economies. We first study an analytic example for the plain-vanilla Taylor (1980) model. We then quantify price selection in a calibrated multisector version of the Golosov and Lucas (2007) model. Starting with the case of identical sectors, i.e., where aggregate and sector-specific moments are equal, we document that the Golosov-Lucas model exhibits strong price selection, −0.341, broadly in line with our evidence at the stratum level.

We then introduce heterogeneity across sectors and ask whether the model can match the cross-sectional relationship between price selection and frequency of price changes that we document in the data and whether aggregation weakens price selection. Consumption sectors differ along two dimensions: the degree of nominal price rigidity and the degree of price selection. We associate sectors in each model with 66 basic classes in the U.K. data, where the fraction of price changes varies between 0.033 and 0.404 and the associated sector-level price selection ranges between −0.198 and −0.482. Indeed, the multisector Golosov-Lucas model matches the cross-sectional pattern of price selection and price stickiness quite well. It also delivers weaker aggregate selection, although to a lesser extent than we estimate in the data. This happens for two reasons. First, price changes from more flexible sectors are more heavily represented in the cross-section relative to price changes from stickier sectors, so aggregate price selection puts larger weight on sectors with relatively weak selection; this mechanism was explained in Kara (2015) and Carvalho and Schwartzman (2015). Second, price adjustments in different sectors are imperfectly correlated as they close price gaps of different magnitudes (larger gaps in less flexible sectors), so their joint impact on the aggregate price is smaller.

Finally, we show that in standard sticky-price economies our measure of price selection maps one to one into the extent of monetary non-neutrality. To that end, we rely on a generalized model that nests Golosov and Lucas (2007) and Calvo (1983) as limiting cases. The additional degree of freedom allows us to vary the extent of price selection between the level delivered by the Golosov-Lucas model and zero price selection, i.e., the Calvo model. The tight link between price selection and monetary non-neutrality underscores that our proposed measure is useful not only because

[2]Some related empirical work focuses on the price pass-through of firm- or product-level shocks to marginal costs and also provides a wide range of estimates: from none or very small (Carlsson, 2016) to virtually full pass-through (Eichenbaum, Jaimovich, and Rebelo, 2011). Gagnon, López-Salido, and Vincent (2012) study the effect of large inflationary shocks on the timing of price changes using Mexican CPI data: they provide evidence for the response of the timing of price changes to inflation shocks, although they do not identify how much of this response is due to selection effects.

it is model free, but also because it captures the key role of selection effects in determining the inflation-output trade-off. We exploit this characteristic to study whether price selection interacts with real rigidities in the sense of Ball and Romer (1990) and Kimball (1995). For a given degree on nominal price stickiness, real rigidities are known to increase the price contract multiplier and thus the degree of monetary non-neutrality. We demonstrate that these effects of real rigidities on monetary non-neutrality are orthogonal to the effects induced by price selection. Hence, our findings bring important lessons for our understanding of monetary non-neutrality in sticky-price models. Non-neutrality can be thought of as a function of the frequency of price changes, the degree of selection, and the strength of real rigidities. The frequency of price changes can be measured directly from micro price data without the need to identify either selection effects or real rigidities. We show that the second determinant of non-neutrality—price selection—can also be estimated directly from micro price data, without the need to identify its other determinants. This finding reinforces the importance of identifying real rigidities. While the literature provides indirect estimates based on applied theoretical models matched to observed micro price behavior (e.g., Gopinath and Itskhoki, 2011; Kryvtsov and Midrigan, 2013; Klenow and Willis, 2016), it may prove possible to develop a model-free approach for identifying real rigidities, as we pursue here with regards to price selection.

The paper proceeds as follows. The concept of price selection is introduced in Section 2. Section 3 explains the data sources and empirical definitions. Section 4 discusses how we identify and measure price selection in U.K., U.S. and Canadian micro data. Section 5 distils the implications of the empirical findings for sticky-price models. Section 6 concludes.

2 Definition of price selection

2.1 Inflation decomposition

Consider an economy with a continuum of goods, and let $G_t(p)$ denote the distribution of prices in period t (all prices are in logs). The aggregate price level in period t, P_t, can be defined as the mean of G:

$$P_t = \int_{-\infty}^{\infty} p \, dG_t(p).$$

Inflation, therefore, can be fully characterized by the sequence of price distributions $\{G_t(p)\}$:

$$P_t - P_{t-1} = \int_{-\infty}^{\infty} p \, d\left|G_t(p) - G_{t-1}(p)\right|. \tag{1}$$

We can simplify this expression by focusing on prices that change from $t-1$ to t. Let $\Lambda_{t|t-1}(p)$ denote the measure of prices in the interval $[p, p+dp]$ in period $t-1$ that adjust between periods $t-1$ and t; and let $H_{t|t-1}(p' \mid p)$ denote their distribution in period t. The measure of prices in the

interval $[p, p + dp]$ in period t is

$$G_t(p)\,dp = \left(1 - \Lambda_{t|t-1}(p)\right) dG_{t-1}(p) + \left[\int_{-\infty}^{\infty} H_{t|t-1}(p\,|\,\widetilde{p})\,\Lambda_{t|t-1}(\widetilde{p})\,dG_{t-1}(\widetilde{p})\right] dp. \tag{2}$$

The first term on the right-hand side is the measure of prices that were in the interval $[p, p + dp]$ in period $t-1$ and did not change. The second term is the measure of prices that did change to the level in the interval $[p, p + dp]$ in period t. To obtain this measure, first, for each price $\widetilde{p}$ in the domain, compute the measure of prices from an interval $[\widetilde{p}, \widetilde{p} + dp]$ in period $t-1$ that are adjusted to a point in the interval $[p, p + dp]$ in period t. This measure is given by $H_{t|t-1}(p\,|\,\widetilde{p})\,\Lambda_{t|t-1}(\widetilde{p})\,dG_{t-1}(\widetilde{p})$. Second, sum across all prices $\widetilde{p}$. Using (2) to substitute for $G_t(p)\,dp$ in (1) yields

$$P_t - P_{t-1} = -\int_{-\infty}^{\infty} p\,\Lambda_{t|t-1}(p)\,dG_{t-1}(p) + \int_{-\infty}^{\infty} p\left[\int_{-\infty}^{\infty} H_{t|t-1}(p\,|\,\widetilde{p})\,\Lambda_{t|t-1}(\widetilde{p})\,dG_{t-1}(\widetilde{p})\right] dp. \tag{3}$$

The first term on the right-hand side is (the negative of) the weighted mean of time-$(t-1)$ level of those prices that change between periods $t-1$ and t, and the second term is their weighted mean time-t level, with both means weighted by the measure of adjusting prices.

It is convenient to rewrite expression (3) in terms of price levels conditional on price adjustment. Let Fr_t denote the measure of price changes in period t. P_t^{pre} is the average time-$(t-1)$ level of prices that adjust between periods $t-1$ and t relative to the aggregate price level at $t-1$ ("preset price-relative"), and P_t^{res} denote their average time-t level relative to the aggregate price level at $t-1$ ("reset price"):

$$\begin{aligned}
Fr_t &= \int_{-\infty}^{\infty} \Lambda_{t|t-1}(p)\,dG_{t-1}(p), \\
P_t^{pre} &= \int_{-\infty}^{\infty} p\,\Lambda_{t|t-1}(p)\,Fr_t^{-1}\,dG_{t-1}(p) - P_{t-1}, \\
P_t^{res} &= \int_{-\infty}^{\infty} p\left[\int_{-\infty}^{\infty} H_{t|t-1}(p\,|\,\widetilde{p})\,\Lambda_{t|t-1}(\widetilde{p})\,Fr_t^{-1}\,dG_{t-1}(\widetilde{p})\right] dp - P_{t-1}.
\end{aligned}$$

Then, inflation decomposition (3) can be written as

$$\pi_t \equiv P_t - P_{t-1} = Fr_t\left(P_t^{res} - P_t^{pre}\right). \tag{4}$$

Price selection is identified by comovement between P_t^{pre} (the average level of adjusting prices relative to the average level of all prices) and the intensive margin of inflation.

2.2 Comparisons to alternative inflation decompositions

Decomposition (4) provides a novel spin on the decomposition in Klenow and Kryvtsov (2008), who cast inflation as the product of the average fraction of price changes and their average size conditional on adjustment. Our decomposition represents the average size of price changes, DP_t, as the difference between the average price level of newly set prices and their average level prior to adjustment, $DP_t \equiv P_t^{pres} - P_t^{pre}$.[3]

Bils, Klenow, and Malin (2012) study the relationship between inflation and "reset price inflation." They define reset price inflation as the estimated rate of change of new prices set by the subset of price changers. Since the subset of price changers varies from month to month, reset price inflation depends on both changes in the reset price levels and price selection. Therefore, their approach does not separately identify price selection and its impact on inflation dynamics. Using simulations of the Smets and Wouters (2007) business cycle model, Bils, Klenow, and Malin (2012) show that it is inconsistent with joint dynamics of inflation and reset price inflation in the U.S. data. Kara (2015) shows that these dynamics can be partially reconciled if business cycle models incorporate different degrees of price flexibility across consumption sectors. Price selection makes inflation more sensitive to shocks, and thus may partly drive Bils et al.'s reset price inflation.

Following a model-based approach, Caballero and Engel (2007), Costain and Nakov (2011a), and Dotsey and Wolman (2018), propose decompositions of the inflation response to a monetary shock. This response is due to the cumulative impact of desired log price adjustments (price gaps), $p_i - p_i^*$, and can be decomposed into the contributions from changes in the size of adjustments by those prices that adjust regardless of the shock (the intensive margin) and from the changes in the fraction of price increases and decreases caused by the shock (the extensive margin). These definitions must rely on model assumptions about the process for desired price levels, p_i^*, and the conditional probability of adjustment as a function of the price gap. While this approach is well suited for demonstrating theoretical implications of selection effects, it is less useful for empirical assessment because the unobserved desired price level is difficult to measure in the micro data.[4] Caballero and Engel (2007) argue that in theory, selection effects are neither necessary nor sufficient to increase the response of inflation to a nominal shock and propose instead focusing on the extensive margin. They clarify, however, that the effect of the extensive margin stems from a combination of selection of price adjustments and their respective impacts on the average price response to a common nominal shock.[5]

[3] Klenow and Kryvtsov (2008) and Nakamura and Steinsson (2008) decompose the variance of DP_t into terms due to price increases and decreases. Using U.S. CPI micro data, they find that price increases play an important role in inflation fluctuations, while the role of price decreases may depend on the definitions of the time series and other controls.

[4] Carlsson (2016) uses the producer price and cost micro data from Sweden to estimate firm-specific marginal cost changes (and therefore p_i^*); he finds a weak response of the timing of individual price changes to firms' marginal costs. In contrast, Eichenbaum, Jaimovich, and Rebelo (2011) find an almost perfect pass-through of cost to prices using scanner data for retail prices.

[5] Gagnon, López-Salido, and Vincent (2012) provide evidence of the quantitative importance of the extensive margin using Mexican CPI data in response to large nominal shocks—peso devaluation in 1994 and VAT hikes in 1994 and 2010.

In contrast to these approaches, our method is model free, requiring only information about price adjustments at the micro level, and it does not mix in the other adjustment margins, such as reset price changes or the extensive margin. Decomposition (4) focuses solely on selection of prices that adjust from month to month—aggregating price *levels* for those prices that adjust: the average starting and ending price levels of adjusting prices (relative to the aggregate price) are what we call preset and reset price levels. Their difference, multiplied by the fraction of price adjustments, is identically equal to inflation. The contribution of movements in the preset price-relative (P_t^{pre}) to inflation dynamics then identifies price selection.[6]

3 U.K., U.S. and Canadian micro data

To measure the relationship between inflation and reset and preset price levels, we need data on price changes at the level of individual goods and services. We employ three datasets for the United Kingdom, the United States, and Canada. The datasets from the U.K. Office for National Statistics (ONS) and Statistics Canada provide prices for goods and services collected monthly from retail outlets used for the construction of the consumer price index (CPI) in these countries. The Symphony IRI dataset provides weekly scanner transactions data for grocery stores in the United States. Unlike ONS and Statistics Canada datasets that provide prices posted by retailers, the IRI dataset provides transaction prices. To the extent possible, our treatments of these datasets make the statistics comparable. The U.K. dataset has a broader coverage than the IRI dataset, and it is also available online, unlike the Canadian dataset, for which we have confidential access. We therefore rely extensively on the U.K. dataset for the multitude of our robustness checks. We also describe it in more detail below. The three datasets provide rich coverage of micro price adjustment in three advanced economies, serving as a compelling source of evidence of price selection (see Table 1).

3.1 U.K. CPI micro data

The dataset is compiled from the survey of prices for goods and services that are included in the household final monetary consumption expenditure component of the U.K. National Accounts. The survey includes prices for more than 1,100 individual goods and services a month, collected from more than 14,000 retail stores across the United Kingdom. The survey excludes the housing portion of consumer prices, such as mortgage interest payments, house depreciation, insurance and other house purchase fees. Expenditures for purposes other than final consumption are also excluded, e.g., those for capital and financial transactions, direct taxes, or cash gifts. The portion of the data published on the ONS website includes only locally collected prices, covering about 57% of the U.K. CPI basket.

[6] In Supplementary Material (Section D) we provide intuition on the workings of selection effects in sticky-price models using the Calvo and Golosov-Lucas models as examples. We also illustrate how our model-free measure of price selection accurately captures the implications of selection effects in these models.

Most prices are collected monthly, except for some services in household and leisure groups, and seasonal items. The sample period includes 236 months, from February 1996 to September 2015. The total number of observations is over 24 million, or about 100,000 per month.[7] Prices are collected across 12 geographical regions, e.g., London, Wales, East Midlands. There are four levels of sampling for local price collection: locations, outlets within location, product categories, and individual product varieties. For each geographical region, locations and outlets are based on a probability-proportional-to-size systematic sampling, with a size based on the number of employees in the retail sector (locations) and the net retail floor space (outlets). The dataset contains prices collected locally in around 150 locations with an average of more than 90 outlets per location.

Product or service categories—or "representative items"—are selected based on a number of factors, including expenditure size and product diversity, variability of price movements, and availability for purchase throughout the year (except for certain goods that are seasonal). There are currently more than 1,100 categories in the basket. Examples of categories include onions, Edam, envelopes, men's suit (ready-made), electric heater, single beds. Finally, for each category-outlet-location, individual products and varieties are chosen by price collectors based on their shelf size and regular stock replenishment.

For each category, ONS stratifies the sample by 22 strata, given by region and shop type pairing. For each category and stratum, the ONS dataset provides sampling weights that reflect that category-stratum's relative importance in households' consumption expenditures.[8] For constructing the CPI, ONS first constructs elementary price indices for each product category-stratum bin by taking geometric means of all prices within the bin, with equal weights. These elementary indices are then aggregated into the CPI using consumption expenditure weights.[9]

Throughout the paper, we provide two alternative treatments of price changes at the individual product level. First, we distinguish price changes associated with temporary price discounts (sales). While sales are relatively infrequent—4.6% per month in the United Kingdom—they usually come with much larger and shorter-lived price swings than regular prices. We adopt ONS' definition of sale prices as temporary reductions on goods that are likely to be available again at regular prices or as end-of-season reductions. When the posted price is discounted, the unobserved regular price

[7] A detailed description of the CPI data sampling and collection can be found in ONS (2014) and Clews, Sanderson, and Ralph (2014). The price quote data are available via the ONS website: http://www.ons.gov.uk/ons/datasets-and-tables/index.html. Recent related work and additional details on data cleaning can be found in Kryvtsov and Vincent (2017) and Chu et al. (2018).

[8] Categories in the CPI are classified into 71 classes, according to the international classification of household expenditure, Classification of Individual Consumption by Purpose (COICOP). A CPI class represents a basic group category, such as meat, liquid fuels, or new cars. Category and class weights are calculated based on the Household Final Monetary Consumption Expenditure (HFMCE) and the ONS Living Costs and Food Survey (LCF). Changes in the expenditure weights over time reflect changes in the expenditure composition of households' consumption baskets. Using class, category, stratum and shop type weights, we follow ONS methodology to construct observation-specific weights for our sample.

[9] The geometric mean, also known as the Jevons index, is used for calculating an elementary price index for CPI in the United States and Canada, whereas in the United Kingdom, a mixture of geometric mean and average of price relatives (the Dutot index) is used. See Diewert (2012) for a detailed discussion of various CPI measures in the United Kingdom. To keep our statistics directly comparable across country datasets, we use geometric mean elementary indices everywhere.

equals to the posted price in the month preceding the first month of the sale; it is equal to the posted price if there is no sale. These definitions are reliable for describing sales behavior and are commonly used in the literature.[10]

Second, we differentiate price changes associated with product substitutions. When previously collected price-product is no longer available to a field agent, they make a substitution for another product from the same category. Such substitutions—5.6% per month in the United Kingdom—are more commonly associated with price increases (68% of price changes during substitutions).[11] Symphony IRI data contain prices for uniquely defined products, and therefore we do not apply this treatment to these data.

3.2 Statistics Canada CPI data

The Consumer Price Research Database (CPRD) is compiled by Statistics Canada from price surveys used to construct the non-shelter portion of the Canadian CPI. The dataset contains information about prices for goods and services posted by retail outlets across Canada from February 1998 to December 2009, or 143 months. Overall, the CPRD contains more than 8.4 million observations (almost 60,000 per month) and covers about 61% of the consumption basket underlying the CPI. Since the CPRD is a dataset of individual prices, it excludes goods for which prices are aggregated indexes, such as utility rates, insurance premiums, transportation fares, sport and theater tickets, books and newspapers, entertainment CDs and DVDs, and computer equipment.

Similar to ONS, Statistics Canada defines a product category (representative item)—a single commodity, such as potatoes, yogurt, gas barbecues, women's gloves, oil filters—selected to represent a basic class of goods and services in the index. There are 705 specific product categories in the dataset. The selection of these items takes into account the following criteria: the price movement of the item should represent the price movement of the given class, and the item has to be available on the market for a reasonable length of time.

Prices are collected from a variety of retail outlets, including supermarkets, specialty shops, department stores, garages, dental offices, and salons. In most cases, the main determining factor in the selection of outlets is the value of sales revenues for the items being priced. However, geographic dispersion and outlet type are also important factors to be considered. Pricing information is collected in up to 92 urban centres across Canada, generally in urban centres with a population of 30,000 or more. Due to confidentiality restrictions for this dataset, strata are defined by a coarser geographical definition, spanning 13 Canadian provinces and territories.

Like the U.K. dataset, the Canadian dataset provides flags for the months corresponding to a sale (9.0% of monthly observations) or to a product substitution (3.5%). We therefore treat those observations the same way we treat the U.K. dataset.

[10] Nakamura and Steinsson (2008) demonstrate that sales affect the measurement of the extent of nominal price stickiness in the U.S. CPI data. Kryvtsov and Vincent (2017) provide evidence of the countercyclical variation in the number of sales in the United Kingdom and United States; they also discuss different definitions of sales in the data.

[11] Klenow and Malin (2010) provide an overview of the incidence of sales and substitutions and their implications for price adjustment. Bils (2009) and Kryvtsov (2016) document the occurrence of price substitutions and assess the extent of the associated quality bias in the U.S. and Canadian CPI data, respectively.

3.3 Symphony IRI Inc. data for the United States

Symphony IRI is a marketing and market research dataset that contains scanner data, product description data, store data and household data.[12] The scanner data are provided at a weekly frequency for a panel of 31 grocery products, such as beer, coffee, milk, razors, laundry detergent, and frozen pizza. To make the IRI dataset comparable to the CPI datasets, we convert weekly observations into monthly by using the first available weekly observations from that month. In all, the dataset contains around 1.5 billion observations, or 36.2 million monthly observations, covering the span of 132 months, from January 2001 to December 2011, or around 274,000 per month.

The data are provided for grocery stores in 50 U.S. metropolitan areas. Each store has a unique identifier, so its prices and quantities can be tracked over time. Scanner data include the revenue and quantity for weekly purchases for each product, identification for the product, display indicator and sale indicator. For each individual product in a product category, we define a unique product identifier by matching UPC codes for that product with product description (e.g., Budweiser lager 355 mL). We include only stores belonging to chains that exist throughout the entire sample period. We exclude products that belong to a store's private label (their coding was changed by IRI in 2007 and 2008), products that have fewer than two observations per week, and observations with a unit price less than \$0.10.

Similar to strata in the ONS and Statistics Canada data, we define an elementary bin in IRI data to be represented by a category and metropolitan location. The share of nominal revenues over the sample period in total revenues over the sample period is used as a stratum weight. In a given week, unit prices for each UPC are constructed by dividing weekly revenue by the quantity sold. For weeks in which transactions occur during price discounts, regular unit prices are equal to the last observed regular unit price. Around 9.0% of monthly observations are price discounts.[13]

3.4 Empirical definitions

The micro data used in this paper present us with two challenges for accurate measurement of price selection: heterogeneity across products, locations and stores, and measurement error. These issues are known to bias the estimates of price moments in the data and may as well apply to measurement of price selection.[14]

To deal with these issues, we apply inflation decomposition (4) at the category-stratum level — the most disaggregate available level in our datasets. Statistical agencies stratify their samples to improve representatativeness of prices they collect and reduce sample noise. We also exclude ob-

[12]More details are provided in Bronnenberg, Kruger, and Mela (2008).

[13]Coibion, Gorodnichenko, and Hong (2015) use the Symphony IRI dataset to study retail prices and household expenditures across metropolitan areas, finding that reallocation of expenditures across retailers during local recessions lowers average prices paid by consumers.

[14]For example, Alvarez, Le Bihan, and Lippi (2016) show how heterogeneity and measurement error introduce an upward bias in measured kurtosis of price changes. Heterogeneity of price behavior across products, stores, and locations has been well documented, including not only the differences in the frequency and size of price changes, but also the incidence of price discounts, product churning, and stockouts. Klenow and Malin (2010) and Nakamura and Steinsson (2013) provide detailed reviews of microeconomic evidence on price dynamics and the extent of heterogeneity.

servations with log-price changes in the top percentile of absolute log price changes within each category-stratum; this helps to filter out coding errors or other outliers in month-to-month price movements (see Alvarez, Le Bihan, and Lippi, 2016). Finally, we exclude strata with less than 10 price changes over the sample period.

The empirical counterparts of the four variables entering inflation decomposition (4) are constructed as follows. Let p_{ist} denote log price of product i in category-stratum s and in month t, where subscript i uniquely identifies an individual product in a particular location (and also type of retail outlet in the U.K. data). Let P_{st} denote the arithmetic mean of log prices for all products with price observations in both periods t and $t-1$. Let N_{st} be the number of price observations in stratum s in month t. Let I_{ist} be an indicator of a price change for product i in month t, $I_{ist} = 1$ if $p_{ist} - p_{is,t-1} \neq 0$, and 0 otherwise. Noting that $p_{ist} - p_{is,t-1} \equiv I_{ist}\left(p_{ist} - P_{s,t-1} + P_{s,t-1} - p_{is,t-1}\right)$, we can write inflation in category-stratum s in month t as the mean of log price changes in that bin and month and express it identically as follows:

$$\begin{aligned} \pi_{st} &\equiv \frac{\sum_i (p_{is,t} - p_{is,t-1})}{N_{st}} \\ &\equiv \underbrace{\frac{\sum_i I_{is,t}}{N_{st}}}_{Fr_{st}} \times \left[\underbrace{\frac{\sum_i I_{is,t}\left(p_{ist} - P_{s,t-1}\right)}{\sum_i I_{is,t}}}_{P_{st}^{res}} - \underbrace{\frac{\sum_i I_{is,t}\left(p_{is,t-1} - P_{s,t-1}\right)}{\sum_i I_{is,t}}}_{P_{st}^{pre}} \right], \end{aligned} \tag{5}$$

Equation (5) takes the same form as (4):

$$\pi_{st} \equiv Fr_{st} \cdot \underbrace{\left[P_{st}^{res} - P_{st}^{pre}\right]}_{DP_{st}}, \tag{6}$$

where Fr_{st} is the mean fraction of products in category-stratum s changing price in month t; reset price P_{st}^{res} is the mean of log prices that changed in month t relative to the corresponding stratum population mean log price in month $t-1$; and preset price P_{st}^{pre} is their corresponding mean level *prior* to change, in period $t-1$, relative to stratum s population mean log price level in month $t-1$. The term in brackets is the average size of prices that change in month t, $DP_{st} \equiv P_{st}^{res} - P_{st}^{pre}$. Decomposition (6) nests the breakdown of inflation into extensive and intensive margins (represented by Fr_{st} and DP_{st}, respectively), proposed by Klenow and Kryvtsov (2008), namely, $\pi_{st} \equiv Fr_{st} \cdot DP_{st}$. In our empirical analysis in the next section, we assess price selection for stratum-level time series, using the variables defined in (6).

Table 1 provides descriptive statistics for the U.K., U.S. and Canadian data for the case that excludes price changes due to sales and substitutions.[15] Regular price inflation in both the United Kingdom and Canada averaged 0.12% and 0.18% per month, or around 1.5% and 2.2% per year, during respective sample periods. In the U.S. grocery data, it was twice as high, at 0.29% per month, or 3.5% per year. In a given month, 12.7% of regular prices change in the United Kingdom,

[15]Tables A.1–A.3 in Supplementary Material compare descriptive statistics across different treatments of sales and substitutions.

or around once every 8 months. Prices in Canada and grocery prices in the United States change 21.7% and 22.3% of the time, or once in every 4 months on average. An average magnitude of price changes therefore is 0.96%, 0.84%, and 1.31% in the United Kingdom, Canada, and the United States, respectively. Reset and preset price levels are expressed as % deviations from the population average, and therefore their averages may vary depending on inflation experiences over the samples in the country datasets. Indeed, both levels are positive for the United Kingdom (1.12% and 0.76%) and negative for Canada (−0.20% and −0.72%) and the United States (−2.19% and −2.90%). The remaining rows in Table 1 provide auxiliary statistics that we use for calibrating and evaluating sticky-price models.

4 Price selection in the U.K., U.S. and Canadian micro data

4.1 Evidence at the category-stratum level

To quantify the degree of price selection at a category-stratum level, we estimate the following baseline empirical specification:

$$P_{st}^{pre} = \gamma DP_{st} + \delta_{cal} + \delta_s + error, \tag{7}$$

where the dependent variable, P_{st}^{pre}, is the preset price level for a product category-stratum s in month t, and the independent variable of interest is the average size of price changes for category-stratum s in month t, DP_{st}. Since, by definition, $DP_{st} \equiv P_{st}^{res} - P_{st}^{pre}$, the absolute value of the estimated regression coefficient γ is equal to the estimated fraction of DP_{st} variance accounted for by variation in preset price level P_{st}^{pre}, with the remaining fraction due to reset price level changes. Hence, we adopt the estimated $\hat{\gamma}$ as our measure of price selection. Values of $\hat{\gamma}$ that are significantly different from zero are interpreted as evidence of price selection; negative (positive) values indicate that price selection increases (decreases) the sensitivity of inflation to underlying disturbances. Our baseline specification (7) also includes calendar-month fixed effects δ_{cal}, and category fixed effects δ_c. Equation (7) is estimated by a pooled weighted least squares regression, with weights given by the share of expenditures in category-stratum s in month t (ω_{st}).[16]

Table 2 provides the results of this estimation for all three datasets. For our baseline, we consider the case with regular prices and exclude price changes due to product substitutions. The estimated price selection is −0.371 for the United Kingdom, −0.360 for the United States, and −0.285 for Canada, all statistically significant at a 1% level (column 1).[17] The estimates are largely consistent across the three countries; a somewhat lower absolute value for Canada (i.e., weaker selection) can be attributed to aggregation across locations within a province (see Section 4.3). The degree of

[16] We exclude strata with price selection in the top and bottom 0.5 percentile from the analysis. Stratum-specific estimates of price selection are presented below.

[17] Table A.4 in Supplementary Material provides comparisons with alternative standard errors: Driscoll and Kraay (1998), clustered by strata, and clustered by month. The results remain highly significant. Furthermore, including a constant in the regression changes the estimated value of the price selection coefficient by only about 0.0003, so it is immaterial for the results below.

price selection is virtually unchanged when we allow calendar-month fixed effects, add category-specific linear trends, or consider unweighted regressions (columns 2 through 4). To visualize price selection, Figure 1 provides scatter plots for the largest strata in nine selected product categories in the United Kingdom, including oil, milk, hotel, and cigarettes. For each category, each point on the plot represents a monthly observation for the average size of price changes (x-axis) and preset price level (y-axis). Hence, each plot demonstrates joint variation of P_{st}^{pre} and DP_{st} across months for a given stratum. There is substantial variation in both variables for each category-stratum and across strata, and they tend to correlate negatively, pointing to the prevalence of price selection that amplifies stratum-level inflation variation.[18]

Column 5 in Table 2 provides the results for all price changes—both regular and those associated with price discounts. Including price discounts makes price selection at a category-stratum level slightly weaker for the United Kingdom and the United States, –0.333 and –0.303, respectively, and slightly stronger for Canada, –0.327. Including price changes associated with product substitutions, shown in column 6, makes price selection a bit stronger in the United Kingdom, and slightly weaker in Canada, –0.415 and –0.268; substitutions do not arise in the IRI dataset. Hence, price discounts and substitutions do not appear to materially influence price selection at a stratum level.

To what extent does price selection differ across categories? Figure 2 shows the weighted histogram of price selection coefficients estimated individually for each category-stratum in the United Kingdom, for the case with regular prices and no substitutions and allowing calendar-month effects. The empty red bars show the weights for all estimated coefficients. To focus on the coefficients that are accurately estimated, we also plot the weighted histogram for the coefficients that are statistically different from zero at 5% significance level (solid bars). Almost all coefficients (93% of the weight) are negative, indicating price selection that increases sensitivity of stratum-level inflation to shocks; the remaining 7% of strata have selection of the opposite sign, and therefore it mutes inflation fluctuations in those strata. The weighted mean across all price selection values (all non-zero values) is –0.392 (–0.396), and the weighted median is lower at –0.400 (–0.402) since the distribution of price selection is slightly negatively skewed. These weighted estimates are close to the estimate of stratum-level price selection obtained in the baseline empirical specification.

4.2 Price selection and price-setting moments

How does price selection vary with pricing behavior? We explore the richness of the datasets to answer this question and provide more guidance for business cycle models, discussed in Section 5. We modify the panel regression (7) by allowing price selection to vary with price adjustment

[18] Variation in the average size of price changes, DP_{st}, accounts for most of the variation in inflation, as pointed out by Klenow and Kryvtsov (2008)—71% for the United Kingdom at a category level. Hence, if we regress P_{st}^{pre} (multiplied by the mean fraction of price changes Fr_c) on inflation π_{ct}, instead of the average size of price changes DP_{ct}, the estimated coefficients remain significant and negative. We also experimented taking out stochastic trends at a category-stratum level—price selection is stronger by about a third. Finally, we gauged the extent of a high-frequency component of price selection by bandpass-filtering regression variables using the Baxter-King (12, 96, 24) filter. As a result, price selection remains highly statistically significant, although its magnitude is roughly half of the magnitude for estimated with unfiltered data.

moments computed at a stratum level, so that $\gamma = \gamma_1 + \gamma_2 \Gamma_{st}$, where Γ_{st} are price adjustment moments for category-stratum s in month t. We focus on cross-sectional variation and estimate the following empirical specification:

$$P_{st}^{pre} = \gamma_1 DP_{st} + \gamma_2 DP_{st} \times \Gamma_{st} + \delta_t + error, \tag{8}$$

where $DP_{st} \times \Gamma_{st}$ are the interaction terms between DP_{st} and Γ_{st}, and δ_t are time fixed effects. For the interaction terms, we consider five price adjustment moments: the frequency and average size of price changes, Fr_{st} and DP_{st}, the average absolute size of individual price changes, kurtosis of non-zero price changes, and standard deviation of complete price spells.

Table 3 provides the estimation results. For the baseline case with regular prices and no substitutions, price selection across strata is consistent with price selection obtained by exploiting time variation, reported above: −0.367 for the United Kingdom, −0.373 for the United States, and −0.295 for Canada, all highly statistically significant. We visualize our cross-sectional findings in Figure 3, which provides scatter plots for nine selected months in the United Kingdom, for all prices and excluding substitutions. For each month, each point on the plot represents an observation for the largest stratum in a particular category, giving the average size of price changes (x-axis) and preset price level (y-axis). The size of each circle represents that stratum's consumption weight. Hence, each plot shows joint variation of P_{st}^{pre} and DP_{st} across strata in a given month. Similar to the case for time variation, there is substantial variation in both variables across strata in a given month, and they tend to correlate negatively for most months, pointing to common incidence of price selection.

The other columns in Table 3 provide the results for the full specification (8), including all five interaction terms, for the baseline case and for alternative cases incorporating price discounts and product substitutions.[19]

Two robust results emerge for all specifications and across all three datasets. First, price selection is stronger for category-strata where price changes are less frequent, given by the estimated elasticity $\hat{\gamma}_2$ for the interaction term $DP_{st} \times Fr_{st}$. For the baseline case, the estimates imply that in a category-stratum with a 10 percentage point lower fraction of price changes, price selection accounts for a higher fraction of its inflation variance: by 2.2 percentage points for the United Kingdom (from −0.367 to −0.389), by 6.7 percentage points for the United States (from −0.373 to −0.440), and by 5.7 percentage points for Canada (from −0.295 to −0.352). Across all datasets and all treatments, the range of additional price selection due to a 10 percentage point lower frequency of price adjustment lies between 1.9 and 6.7 percentage points, with an average around 4.5 percentage points. The empirical relationship between the degree of nominal rigidity and price selection can be further corroborated by comparing price selection across types of products. For example, we find that Services (the lowest frequency of price changes) and Non-durables (the highest frequency of price changes) feature the strongest and the weakest price selection, respectively.

The second robust finding is that price selection is stronger (weaker) when average price changes

[19] Estimating interaction coefficients separately, instead of all together, does not alter the conclusions. Results are available upon request.

DP_{st} are above (below) average, given by $\hat{\gamma}_2$ for the interaction term $DP_{st} \times DP_{st}$. If the average size of price changes is higher by 5 percentage points, price selection strengthens by 1.5 percentage points for the United Kingdom (from −0.367 to −0.382) and for the United States (from −0.373 to −0.388) and by 2.5 percentage points for Canada (from −0.295 to −0.320). We also find that price selection becomes stronger with $|DP_{st}|$ although the effects are weak quantitatively (not shown in the table); this is consistent with predictions of non-linear menu cost models, where a response to a larger monetary shock leads to a disproportionately larger response of inflation (Burstein, 2006; Alvarez, Lippi, and Passadore, 2017).

Finally, we do not find a robust relationship between price selection and standard deviation of price spell durations or kurtosis of non-zero price changes—the moments underlying the sufficient statistics for the extent of monetary non-neutrality proposed by Carvalho and Schwartzman (2015) and Alvarez, Le Bihan, and Lippi (2016). The sufficient-statistic approach explores theoretical mappings between particular price-setting moments and the size of monetary non-neutrality. Unlike the sufficient-statistic approach, which relies on theory, we provide a direct measure of one of the mechanisms linking the behavior of individual prices to monetary non-neutrality.

4.3 Aggregate price selection

We have provided evidence of significant price selection at elementary levels—for products in the same category and location. This evidence implies that in response to shocks that move stratum-level inflation up, the subset of prices that adjust tend to originate from below-average levels. The key question then is to what degree price selection matters for the response of aggregate inflation to shocks.

Similar to inflation identity at a stratum level (equations (5)–(6)), we can write aggregate inflation in month t as the product of the aggregate fraction of adjusting prices and their average size in month t, and where the latter is represented as the difference between aggregate reset and preset price levels:

$$\pi_t \equiv Fr_t \cdot \underbrace{\left[P_t^{res} - P_t^{pre}\right]}_{DP_t}, \tag{9}$$

where $Fr_t = \sum_s \omega_{st} Fr_{st}$ is the weighted mean fraction of price changes in month t, with stratum expenditure weights ω_{st}, and aggregate reset and preset price levels, $P_t^{res} = \sum_s \omega_{st} \frac{Fr_{st}}{Fr_t} P_{st}^{res}$ and $P_t^{pre} = \sum_s \omega_{st} \frac{Fr_{st}}{Fr_t} P_{st}^{pre}$ are given by the *frequency-weighted* stratum-level means. Weighting stratum-level price indices by their relative frequency reflects the fact that strata with more frequent price adjustments contribute a relatively larger fraction of price changes in the computation of the average size DP_t, as explained in Klenow and Kryvtsov (2008).

To estimate aggregate selection, the regression of preset price level on the average size of price changes is applied to aggregate variables:

$$P_t^{pre} = \gamma DP_t + \delta_{cal} + error, \tag{10}$$

where as before δ_{cal} denotes calendar-month fixed effects.

Table 4 provides the results of this estimation (row "Aggregate"). We find that for regular prices and no substitutions aggregate price selection is substantially weakened: −0.197 for the United Kingdom (versus −0.371 at a stratum level), 0.061 for the United States (−0.360), and −0.003 for Canada (−0.285); and for the United States and Canada the estimates are not statistically significant. Results are very similar when we include price changes during product substitutions.

By contrast, when regression variables are constructed using all prices—both regular and sale prices—a substantial degree of price selection remains at the aggregate level for the United Kingdom: −0.394 (versus −0.371 at a stratum level). For the United States, aggregate selection is also meaningful: −0.140 (versus −0.36 at a stratum level). In both cases, aggregate selection is statistically significant at the 1% level. For Canada, it is still close to zero, −0.039 (versus −0.327 at a stratum level), and it is not statistically significant. Hence, while aggregation of stratum-level regular price changes largely washes out price selection, that is not the case for the United States and the United Kingdom when price discounts are included. This suggests that price discounts represent an important margin of price flexibility in response to macroeconomic shocks. This conclusion is consistent with Kryvtsov and Vincent (2017), who use evidence from the U.K. and U.S. CPI micro data and find that the incidence of price discounts is strongly countercyclical, amplifying fluctuations in the price of aggregate consumption. For Canada, price discounts may not have had their full influence on price selection since the sample ends in 2009, before the period when sales had their largest swings in the United States and United Kingdom.

To glean why price selection may dissipate with aggregation, we estimate regression (10) using weighted means, $\sum_s \omega_{st} I_{st}^{pre}$ and $\sum_s \omega_{st} DP_{st}$, instead of frequency-weighted means. The results, reported in Supplementary Material, show that relative frequency weights account for less than a third of the aggregation effect. This suggests that sources of cross-sectional heterogeneity other than sectoral differences in frequencies of price changes contribute to weakening price selection at the aggregate level.

We also repeat the estimation for two intermediate levels of aggregation using the U.K. data. At a category level, the variables are aggregated across 12 U.K. regions and 2 store types (stores with fewer or more than 10 outlets), using both weighting schemes. This reduces the size of cross-section from 8,914 to 1,037 groups. Price selection is affected very little. Next, at a coarser level yet, we compute the variables by COICOP class, decreasing the cross-section to 66 classes. Again, class level selection is only slightly weaker, −0.361 versus −0.371 at a stratum level for regular prices and no substitutions. Hence, most of price selection goes away with aggregation across (as opposed to within) broad product categories. In the next section, we ask whether standard multisector sticky-price models are consistent with price selection in the data.

5 Price selection in sticky-price models

In this section we compare predictions of standard sticky-price models with the facts presented in the previous section. First, we illustrate the workings of price selection analytically in a plain-vanilla Taylor (1980) model and show that it is qualitatively consistent with some of our empirical findings. Second, we quantify price selection in a multisector version of the Golosov and Lucas (2007) model and show that price selection maps one-to-one into monetary non-neutrality in a generalized framework that nests the Golosov and Lucas (2007) and the Calvo (1983) models as limiting cases.

5.1 Analytical example

We first illustrate the workings of price selection using a simple version of the Taylor (1980) model.[20] Prices are fixed for T periods and price changes are spread over time so that the fraction of adjusting prices is the same in each period t, $Fr_t = \frac{1}{T}$. Log money supply follows a random walk $M_t = M_{t-1} + \varepsilon_t$, with i.i.d. innovations ε_t with variance σ_ε^2. In the simplest case with no strategic complementarities, firms that adjust their price set it to the desired price level, which is equal to the level of the money supply.[21] The aggregate price is simply the mean of the last T realizations of the money supply, $P_t = \frac{M_t + M_{t-1} + ... + M_{t-(T-1)}}{T}$, and inflation is $\pi_t = \frac{M_t - M_{t-T}}{T}$.

In this simple setup, adjusting prices change from the level of money supply T periods ago, M_{t-T}, to the level of money supply in the current period, M_t, so the average size of price changes is the sum of the last T monetary shocks:

$$DP_t = M_t - M_{t-T} = \varepsilon_t + \varepsilon_{t-1} + ... + \varepsilon_{t-(T-1)}.$$

The preset price level measures the distance between the initial level of adjusting prices, M_{t-T}, and the population average price level P_{t-1}:

$$P_t^{pre} = M_{t-T} - P_{t-1} = -\frac{\varepsilon_{t-1} + 2\varepsilon_{t-2} + ... + (T-1)\varepsilon_{t-(T-1)}}{T}, \tag{11}$$

so it is an aggregate of past shocks, with higher weight on older shocks.

The price selection measure is

$$\gamma = \frac{cov\left(P_t^{pre}, DP_t\right)}{var(DP_t)} = \frac{\sigma_\varepsilon^2 \sum_{j=0}^{T-1} \frac{j}{T}}{\sigma_\varepsilon^2 T} = -\frac{1}{2} + \frac{1}{2T}, \tag{12}$$

and so price selection is stronger with price stickiness T, in line with empirical results in Section 4.2. For large T, price selection in the Taylor model explains half of inflation variance. In Supplementary Material (Section C), we provide detailed derivations of price selection in models due to Calvo

[20] The Taylor model exhibits the strongest selection effects within the class of time-dependent pricing models, as shown by Carvalho and Schwartzman (2015).

[21] Idiosyncratic shocks that make firms' desired prices heterogeneous have no aggregate effects in the Taylor (1980) model and do not affect our measure of price selection. Hence, we omit them for clarity of exposition.

(1983), Caplin and Spulber (1987), and Head et al. (2012). We also derive price selection in a class of multisector models that nest Taylor and Calvo pricing as special cases.

To understand why price selection weakens with aggregation, consider, for example, the Taylor model with two equally weighted sectors with different degrees of price flexibility: $T_1 = 2$ and $T_2 = 4$. According to (12), price selection in the two sectors is $\gamma_1 = -\frac{1}{4}$, $\gamma_2 = -\frac{3}{8}$, so that on average, selection at a sector level is $-\frac{5}{16}$. It is straightforward to derive aggregate selection, $-\frac{10}{40}$, which is weaker than sector-average selection. 40% of this aggregation effect is due to a higher proportion of price changes (two out of each three price changes) coming from the sector with more frequent price changes and weaker selection, i.e., Sector 1; this mechanism stemming from dispersion in frequencies of price changes across sectors was explained in Kara (2015) and Carvalho and Schwartzman (2015). The remaining aggregation effect is due to the fact that price adjustments in different sectors are less mutually correlated than in the model with identical sectors, so their joint impact on the aggregate price is smaller. The aggregation result in the model is consistent with empirical results in Section (4.3), where aggregate price selection is weaker than average sector-level selection, in part due to heterogeneity in the frequency of price changes across sectors.

5.2 Multisector model

In our analytical example, we abstracted from fitting the characteristics of the observed price behavior at a micro level, which may be important for assessing quantitative implications of our empirical findings. In this section, we study a multisector version of the Golosov and Lucas (2007) model and compare its predictions with the evidence on price selection at stratum and aggregate levels from Sections 4.1 and 4.3.

The model represents an economy populated by a large number of infinitely lived households and monopolistically competitive producers of intermediate goods. The shocks in this economy are aggregate shocks to the money supply and idiosyncratic productivity shocks. The idiosyncratic shocks follow AR(1) processes with normally distributed i.i.d. innovations, and money supply follows a random walk with drift, also with normally distributed i.i.d. innovations. The demand for product varieties is derived under assumptions of constant elasticity of substitution between consumption goods within and across N consumption sectors; we set this elasticity to 3, in line with recent evidence by Hobijn and Nechio (2018) and with studies of retail price behavior (see Midrigan, 2011). Sectors producing consumption goods differ in the degree of nominal price rigidity. We associate sectors in the model with 66 basic classes in the U.K. data, so the menu cost in each sector is calibrated to match the mean fraction of adusting prices for one basic class in the data. For the baseline case, we also make assumptions on preferences and technology that lead to strategic neutrality of pricing decisions, as usually assumed in menu cost models (Golosov and Lucas, 2007). Model details are provided in Section B of the Supplementary Material.

Parameters of idiosyncratic shocks are chosen to match the average absolute size of price changes, and serial correlation of newly adjusted prices for the United Kingdom reported in Table 1, but we note that the takeaways we develop in this section are not sensitive to the particular combination

of moments. We use regular price changes (excluding substitutions) to compute the weighted mean absolute size of price changes, 12.2%. To compute serial correlation of adjusted prices, we compute a linear trend for each regular price quote line and express prices in terms of percent deviations from the trend. For each month, we then compute a weighted AR(1) correlation coefficient between such prices across months in which they changed. The mean correlation across months is −0.03. We also choose the size of the monetary shocks to match the standard deviation of regular-price inflation in the U.K. data, 0.23%. The remaining parameters are assigned as follows: the discount factor is $0.96^{1/12}$, corresponding to a 4% annualized average real rate of interest. Mean rate of the money growth is 0.12% to have the model match the mean monthly rate of regular price inflation of 0.12%, or 1.5% per year.[22]

5.3 Model results: sector-level selection

We first ask whether the calibrated multisector Golosov-Lucas model can reproduce our findings on price selection at a sector level. Figure 4 provides a scatter plot that contains estimated price selection for 66 basic classes in the United Kingdom CPI data and their predicted values based on weighted linear regression with a constant and average monthly fraction of price changes as regressors, for the case with regular prices and no substitutions. As we documented in Section 4.2, an additional 10 percentage points in the frequency of price changes is associated with price selection that accounts for a smaller fraction of inflation variance, by between 2.2 percentage points (if we abstract from correlation of the frequency with other moments of price adjustment) and 7 percentage points (if we take into account the correlation between the frequency of price changes and other moments). The remaining scatter points in Figure 4 provide sector-level price selection in the 66-sector Golosov-Lucas model.

The model is successful in accounting for both the degree of sector-level price selection and its association with the degree of nominal rigidity across sectors. Mean price selection is significant, −0.341 (Column 2 in Table 5) and in line with empirical values that we document at a disaggregate level for the United States (between −0.303 and −0.369), United Kingdom (−0.333 and −0.415), and Canada (−0.268 and −0.327). Moreover, the calibrated model produces a positive relationship between the frequency of price changes and the degree of price selection across sectors, where an additional 10 percentage points in the frequency of price changes is associated with price selection that accounts for a smaller fraction of inflation variance by 3.6 percentage points—within the empirical range. In Supplementary Material, we show that a multisector Taylor model matches sector-level selection and the relationship between frequency of price changes and the degree of price selection across sectors equally well. We thus conclude that models with strong price selection

[22]For the Golosov-Lucas model, we simulate equilibrium dynamics over 235 months for a given draw of monetary shocks and 10000 draws of idiosyncratic productivity shock. For each simulation we compute the time series for the components of the inflation decomposition (6) and the model counterparts of the empirical moments reported in Table 2. All moments are computed by applying the same definitions as in Section 3.4 to the artificial model-generated data. We repeat this simulation 100 times and report the means of model moments over these simulations. For time-dependent pricing models, presented in Supplementary Material, results are derived analytically, under linear approximation.

at disaggregate levels find support in micro price data.

5.4 Model results: aggregate price selection and monetary non-neutrality

We now turn to model predictions for aggregate selection and the extent of monetary non-neutrality. To highlight how heterogeneity across sectors contributes to aggregate dynamics, we first "shut down" heterogeneity by assuming identical sectors with the frequency of price adjustment equal to the mean frequency of price changes in the data. We then examine how price selection aggregates in the model with heterogeneous sectors.

Aggregate price selection in the multisector Golosov-Lucas model is −0.329, which compares with weighted mean selection of −0.341 (Columns 2-3 in Table 5). Hence, aggregation does weaken price selection in the model, but by a smaller degree than in the data. In the U.K. data, aggregate price selection, −0.197, is about half of the sector-level selection of −0.395, and aggregate selection is around zero in the United States and Canada; in the Golosov-Lucas model, aggregate selection is only around 8% weaker than sector-level selection.[23] In Supplementary Material, we present analogous results for a multisector Taylor model and find that aggregate selection is around 25% weaker than sector-level selection. We also compare the responses of the aggregate price level and consumption to monetary shocks in these models, and illustrate the workings of aggregation in weakening price selection.

To study the link between price selection and monetary non-neutrality, we turn to a generalized economy that nests Golosov and Lucas (2007) and Calvo (1983) models as limiting cases. Firms may have the opportunity to change prices for free at times, as in the Calvo model. The parameter that controls this "Calvo weight" provides an additional degree of freedom that allows us to vary the extent of price selection between the level delivered by the Golosov-Lucas model and zero price selection, i.e., the Calvo model.

We study a sequence of such generalized economies, ranging from the Golosov-Lucas model (i.e., with a Calvo weight of zero) to the Calvo model (i.e., with unit Calvo weight). For each such economy, we compute price selection and different measures of monetary non-neutrality. Importantly, all economies feature strategic neutrality in price setting and the same frequency of price changes, and thus differences in the degree of monetary non-neutrality can be traced to selection. Results are reported in Figure 5 and Table 6. They show that price selection maps one-to-one into monetary non-neutrality. Hence, despite its model-free nature, price selection captures the key role of price

[23] In models, aggregation weakens price selection for two reasons. First, selection is weaker in sectors with more frequent price changes. Since price changes from more flexible sectors are represented more in the cross-section relative to price changes from stickier sectors, the aggregate price selection puts larger weight on sectors with relatively weak selection. Second, concurrent price adjustments in different sectors are imperfectly correlated as they close price gaps of different magnitudes (larger gaps in more inflexible sectors); such smoothing of price selection across sectors lowers its impact on the aggregate price. We estimate that about 43% (42%) of the weakening in price selection is due to frequency dispersion in the Golosov-Lucas (Taylor) model. In the data, however, most of aggregation effect (around 79%) stems from sources of heterogeneity other than in the frequency of price changes. This may be due to the fact that, in our models, the only source of common price variation is due to an aggregate shock, whereas in the data sectoral shocks induce additional common factors for prices within each sector. This tends to reduce the correlation of preset prices across sectors.

selection effects in determining the inflation-output trade-off in standard sticky-price models.[24]

Finally, we ask whether price selection interacts with real rigidities in the sense of Ball and Romer (1990) and Kimball (1995) in determining monetary non-neutrality. For a given frequency of price changes, real rigidities are known to increase the price contract multiplier and thus the degree of monetary non-neutrality. More generally, non-neutrality can be thought of as a function of the frequency of price changes, the degree of selection, and the strength of real rigidities. We show that the effects of real rigidities on monetary non-neutrality are orthogonal to the effects induced by price selection. For brevity, results are presented in Supplementary Material, Section A.

6 Conclusions

We draw several conclusions for sticky-price models. First, multisector models with strong selection at sector level have a better chance of accounting for the evidence on price selection. Nakamura and Steinsson (2010) and, more recently Gautier and Le Bihan (2018), show that implications of such models for the sources of business cycles and the effectiveness of monetary policy can differ drastically from models without price selection or sectoral heterogeneity.

We note that predictions of standard sticky-price models can account only for sector variation of price selection between around 0 and −0.5, which is approximately 60% of the weight in the empirical range shown in Figure 2. Models that exploit additional dimensions of heterogeneity across goods and retailers should have a better chance of fitting the facts. For example, our empirical results suggest that incorporating sector-specific inflation trends or disturbances with a varying degree of volatility should expand the range of price selection in multisector models.

Second, aggregation can significantly reduce selection. Standard models can account for only a small portion of the aggregation effect that is due to the differences across sectors in the frequency and timing of price adjustments. Adding information frictions or an interaction of large sector-specific shocks and non-linearities in these models should increase the level and range of price selection at a sector level, while not affecting aggregate selection as much.

Finally, appropriately measuring price selection allows us to more accurately identify the determinants of monetary non-neutrality. For example, we show that real rigidities and price selection essentially do not interact – at least under standard assumptions – and so their effects on non-neutrality can be studied independently. Our evidence also suggests that one sufficient statistic is unlikely to capture the link between one moment in the micro data and monetary non-neutrality; perhaps, combining the sufficient statistics approach with ours may help to assess the importance of other drivers of monetary non-neutrality, such as real rigidities, large sector shocks, or information frictions.

[24] In Supplementary Material, we also analyze how price selection maps into monetary non-neutrality when comparing different families of models that feature price selection (e.g., Taylor, 1980; and Golosov and Lucas, 2007).

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Table 1: Descriptive statistics

	Statistic	U.K.	Canada	U.S.
	Consumption coverage	Non-shelter goods and services	Non-shelter goods and services	Grocery products
	Sample	1996:02–2015:09	1998:02–2009:12	2001:01–2011:12
	# of months	236	143	132
	# of obs/month	102,801	58,670	274,369
	# of categories	1,152	705	31
	# of strata/category	22 (11 regions x 2 store types)	13 provinces and terrirtories	50 metropolitan locations
(1)	π	0.121	0.182	0.291
(2)	Fr	0.127	0.217	0.223
(3)	$DP = \pi/Fr$	0.955	0.842	1.306
(4)	p^{pre}	1.116	-0.198	-2.191
(5)	p^{pre}	0.761	-0.718	-2.904
(6)	adp	12.22	8.25	8.43
(7)	corr	-0.032	0.164	-0.027
(8)	sd_delta	15.74	10.00	11.21
(9)	kurt	5.73	4.70	5.11
(10)	meandur	5.62	6.94	3.56
(11)	sd_dur	5.33	6.28	4.11
(12)	frac of sales	5.6	9.0	9.0
(13)	frac of subs	4.6	3.5	N/A

Notes: Data are from the U.K. Office for National Statistics CPI database, available at http://www.ons.gov.uk/ons/datasets-and-tables/index.html, the Statistics Canada's Consumer Price Research Database, and the Symphony IRI Inc. Sample period: [UK]: from February 1996 to September 2015; [Canada]: from February 1998 to December 2009; [U.S.]: from January 2001 to December 2011.

The entries are weighted means of stratum-level monthly variables. Observations across strata are based on consumption expenditure weights; observations across months are weighted equally. For computing statistics in rows (1) to (11), price changes due to sales or substitutions are excluded (Tables 1-3 in Supplementary Material provide statistics for other cases). π - inflation, in %; Fr - the fraction of items with changing prices; DP - the size of price changes, in %; P^{pre} (P^{res}) - preset (reset) price level defined as the unweighted means of starting (ending) log price levels for all products in the stratum in each month, expressed as % deviations from the average for all log prices in the stratum; adp - the average absolute size of price changes, in %; corr - serial correlation of newly set prices for an individual product; sd_delta - standard deviation of non-zero price changes for a given stratum, in %; kurt - kurtosis of non-zero price changes for a given stratum; meandur - mean price spell duration (for complete spells), in months; sd_dur - standard deviation of price spell durations for a given stratum (for complete spells), in months; frac of sales - fraction of observations with discounted price; frac of subs - mean fraction of observations with product substitutions.

Table 2: Price selection at a category-stratum level

	Regular prices, excluding subs			Unweighted	All prices	Incl. subs
	(1)	(2)	(3)	(4)	(5)	(6)
A. U.K.						
Price selection	**-0.371*****	**-0.371*****	**-0.369*****	**-0.357*****	**-0.333*****	**-0.415*****
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Calendar-month effects	Y	N	Y	Y	Y	Y
Stratum linear trend	N	N	Y	N	N	N
Number of observations	1,073,089	1,073,089	1,073,089	1,073,089	1,075,108	1,077,371
R^2	0.032	0.032	0.032	0.046	0.039	0.055
B. Canada						
Price selection	**-0.285*****	**-0.284*****	**-0.283*****	**-0.310*****	**-0.327*****	**-0.268*****
	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)
Calendar-month effects	Y	N	Y	Y	Y	Y
Stratum linear trend	N	N	Y	N	N	N
Number of observations	568,264	568,264	568,264	568,264	619,489	604,027
R^2	0.022	0.022	0.022	0.027	0.073	0.018
C. U.S.						
Price selection	**-0.360*****	**-0.363*****	**-0.361*****	**-0.369*****	**-0.303*****	**N/A**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Calendar-month effects	Y	N	Y	Y	Y	
Stratum linear trend	N	N	Y	N	N	
Number of observations	18,402,238	18,402,238	18,402,238	18,402,238	22,930,586	
R^2	0.198	0.200	0.198	0.233	0.281	

Notes: Data sources are described in notes for Table 1. The entries in "Price selection" are the estimated values of the coefficient in the weighted panel regression (7) of monthly stratum preset price levels on the monthly average stratum size of price changes, with stratum fixed effects. Columns (1) to (3) provide estimates for the sample excluding price discounts and product substitutions; column (4) - unweighted regression. Column (5) uses all prices and excludes substitutions. Column (6) includes substitutions, regular prices. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Price selection and price changes across product strata

Independent variables	U.K.				Canada				U.S.		
	Baseline	Baseline	All prices	Incl. subs	Baseline	Baseline	All prices	Incl. subs	Baseline	Baseline	All prices
		With interaction terms				With interaction terms				With interaction terms	
DP_{st}	-0.367***	-0.370***	-0.368***	-0.437***	-0.295***	-0.560***	-0.561***	-0.467***	-0.373***	-0.546***	-0.490***
	(0.002)	(0.010)	(0.009)	(0.008)	(0.003)	(0.013)	(0.013)	(0.009)	(0.000)	(0.000)	(0.000)
Interaction terms											
DP_{st} x Fr_{st}		0.220***	0.193***	0.396***		0.566***	.617***	0.456***		0.668***	0.474***
		(0.012)	(0.010)	(0.011)		(0.011)	(0.011)	(0.007)		(0.001)	(0.000)
DP_{st} x DP_{st}		-0.003***	-0.003***	-0.001***		-0.005***	-0.004***	-0.003***		-0.003***	-0.004***
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
DP_{st} x ADP_{st}		0.001**	0.001***	-0.001***		0.003***	0.002***	-0.001***		-0.001***	-0.001**
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
DP_{st} x Kurt p-chgs$_s$		-0.006***	-0.005***	-0.004***		0.004**	0.000	0.006***		0.001***	0.002***
		(0.001)	(0.001)	(0.000)		(0.002)	(0.002)	(0.001)		(0.000)	(0.000)
DP_{st} x Std p-spells$_s$		-0.005***	-0.012***	-0.001		0.005***	0.009***	-0.000		0.003***	0.001***
		(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)		(0.000)	(0.000)
Number of obs	1,073,089	1,072,899	1,075,029	1,077,315	568,264	567,573	600,427	619,303	18,402,238	18,393,701	1,072,899
R^2	0.033	0.036	0.049	0.059	0.023	0.033	0.027	0.086	0.182	0.224	0.036

Notes: Data sources are described in notes for Table 1. The entries are coefficients in the weighted panel regression (8) of monthly stratum preset price levels on independent variables, with month fixed effects. The column "Baseline" corresponds to the case when price changes due to sales or substitutions are excluded. Other columns break down price selection via interaction with stratum-level variables: Fr_{st} -- mean fraction of price changes in stratum s month t, DP_{st} - mean average size of price changes, ADP_{st} - mean absolute size of price changes, Kurt$_s$ - kurtosis of non-zero price changes in stratum s, Std p-spells$_s$ - the standard deviation of complete price spell durations in stratum s. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Price selection, aggregate time series

Level of aggregation	Number of groups	Regular prices, excluding subs	All prices	Incl. subs
A. U.K.				
Stratum	8941	-0.371***	-0.333***	-0.415***
		(0.002)	(0.002)	(0.002)
Category	1037	-0.385***	-0.359***	-0.404***
		(0.006)	(0.005)	(0.005)
Basic class	66	-0.361***	-0.357***	-0.330***
		(0.016)	(0.013)	(0.014)
Aggregate	**1**	**-0.197*** **	**-0.394*** **	**-0.188*** **
		(0.072)	**(0.065)**	**(0.069)**
B. Canada				
Stratum	9165	-0.285***	-0.327***	-0.268***
		(0.003)	(0.001)	(0.003)
Aggregate	**1**	**-0.003**	**-0.039**	**0.013**
		(0.021)	**(0.028)**	**(0.020)**
C. U.S.				
Stratum	1550	-0.360***	-0.303***	N/A
		(0.000)	(0.000)	
Aggregate	**1**	**0.061***	**-0.140*** **	
		(0.035)	**(0.021)**	

Notes: Data sources are described in notes for Table 1. For row "Stratum" the entries are price selection coefficients at a stratum level replicated from Table 2. Other rows provide price selection for aggregated groups (category, basic class, and aggregate). For the U.K., basic class corresponds to Classification of Individual Consumption by Purpose (COICOP). "Aggregate" rows provide the estimated values of the coefficient in the time-series regression (10) of aggregate preset price level on the aggregate size of price changes, with calendar-month fixed effects. Standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 5: Price selection in the Golosov-Lucas model

Moments	Data	Identical sectors	Heterogeneous sectors
	(1)	(2)	(3)
Fraction of p-changes			
weighted mean	0.121	0.121	0.127
min	0.033	0.121	0.037
max	0.404	0.121	0.446
Sector-level selection			
weighted mean	-0.395	-0.341	-0.357
min	-0.482	-0.341	-0.391
max	-0.198	-0.341	-0.236
Aggregate selection	-0.197	-0.341	-0.329
Aggregation effect	0.198	0.000	0.028
due to freq dispersion	21%	-	43%
due to other factors	79%	-	57%

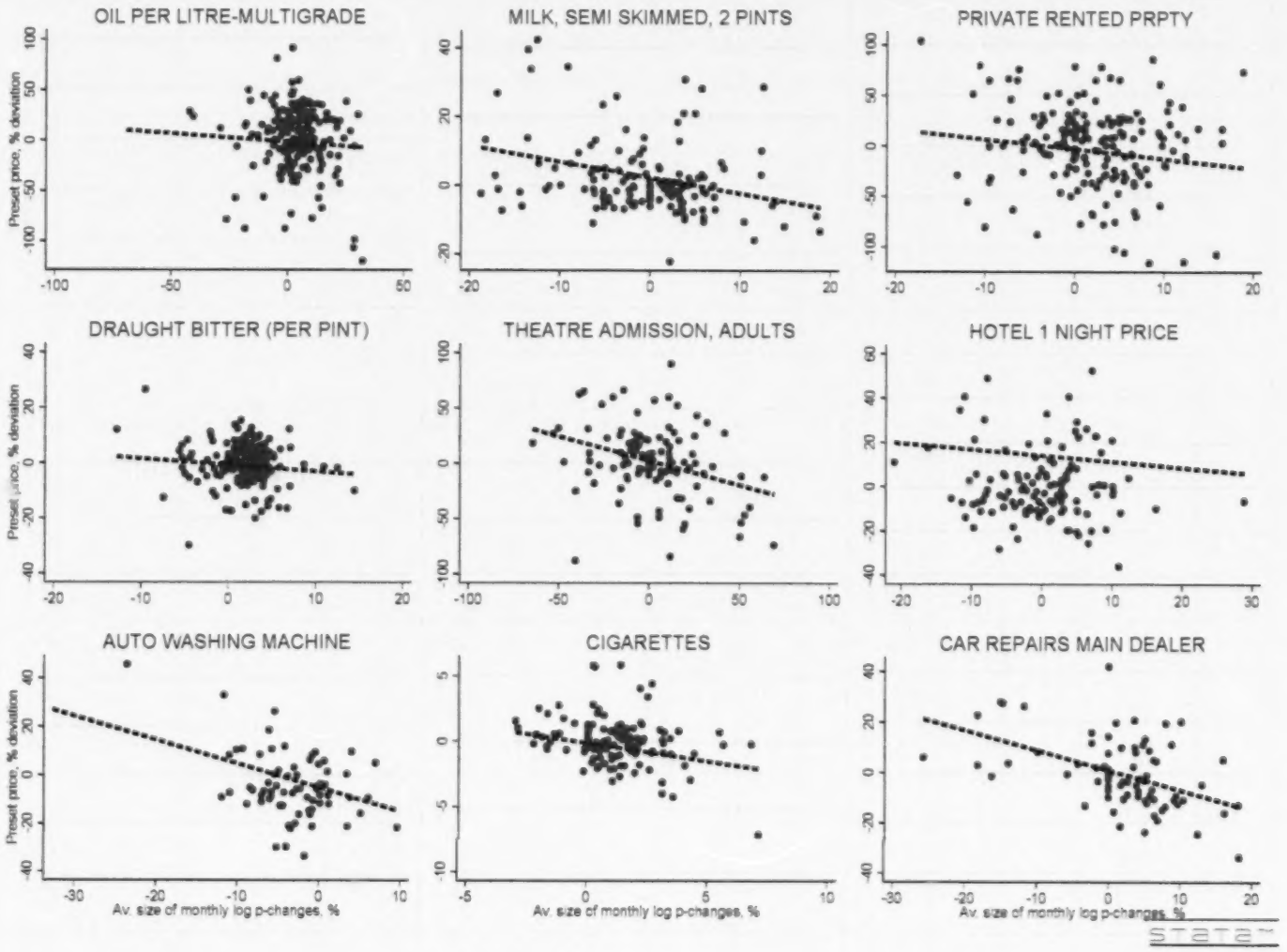
Notes: Data entries correspond to statistics from the 66 basic classes in the U.K. data. Price selection entries in Column (1) correspond to predicted values based on weighted linear regression of sector-level price selection on a constant and sector-level monthly mean fraction of price change as regressors, for the case with regular prices and no substitutions, not controlling for calendar-month effects. Aggregation effect is the difference between aggregate and sector-level selection. The remaining two columns provide the results from the 66-sector Golosov-Lucas models: with identical sectors in Column (2), and with heterogeneous sectors in Column (3). We simulate equilibrium dynamics in each model over 235 months for a given draw of money growth shocks and 10,000 draws of idiosyncratic productivity shock. For each simulation we compute the time series for each of the variables. We repeat this simulation 100 times and report the means of model moments over these simulations.

Table 6: Price selection and monetary non-neutrality in the generalized Golosov-Lucas model

Moments	Weight on Calvo adjustment in generalized Golosov-Lucas model										
	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Fraction of price changes per month, %	12.0	12.2	12.0	12.1	12.1	12.1	12.1	12.1	12.1	12.1	12.1
Weight on Calvo in nested model	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Price selection	-0.346	-0.342	-0.336	-0.326	-0.317	-0.290	-0.272	-0.245	-0.202	-0.137	-0.008
Consumption st.dev., %	0.27	0.28	0.31	0.33	0.36	0.39	0.44	0.49	0.55	0.62	0.74
Consumption ser. corr	0.52	0.55	0.59	0.61	0.64	0.67	0.71	0.75	0.78	0.82	0.86
Half-life of consumption IRF to 1% shock, months	1.07	1.17	1.30	1.41	1.54	1.74	2.02	2.39	2.80	3.48	4.64
Consumption cumulative IRF to 1% shock	1.14	1.26	1.44	1.63	1.86	2.15	2.60	3.22	3.91	5.07	7.17

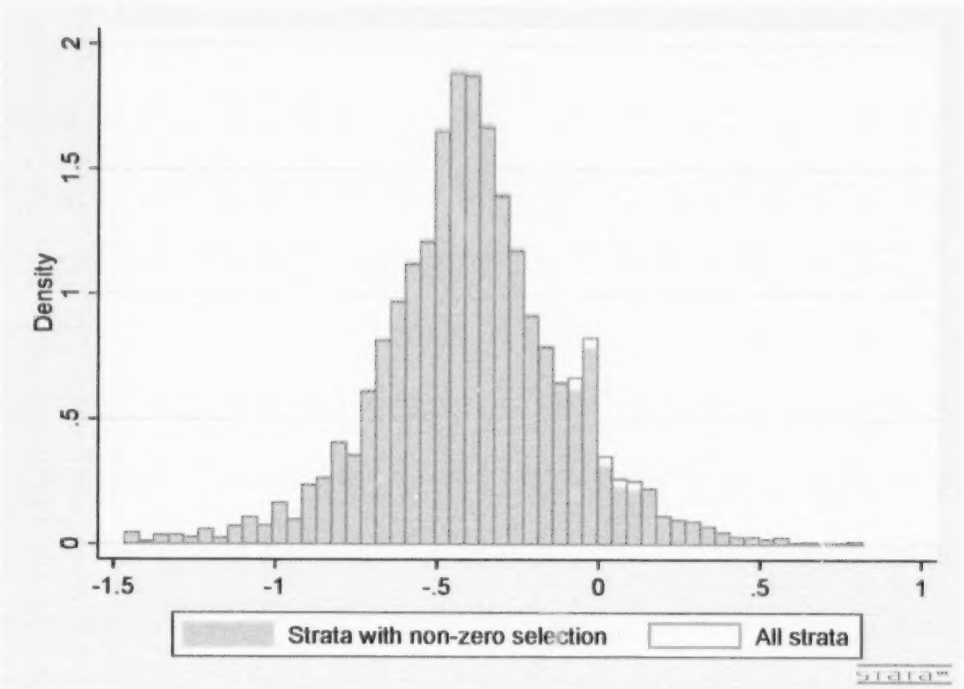
Notes: Entries are results of simulations of generalized Golosov-Lucas model, which nests the Calvo model. Columns correspond to simulations for different weight on Calvo pricing. Each economy is simulated over 235 months for a given draw of a money growth shocks and 10000 draws of idiosyncratic productivity shock. For each simulation we compute the time series for each of the variables. We repeat this simulation 100 times and report the means of model moments over these simulations.

Figure 1: Preset price level and average size of price changes, variation over time for largest strata in selected product categories, U.K. CPI data



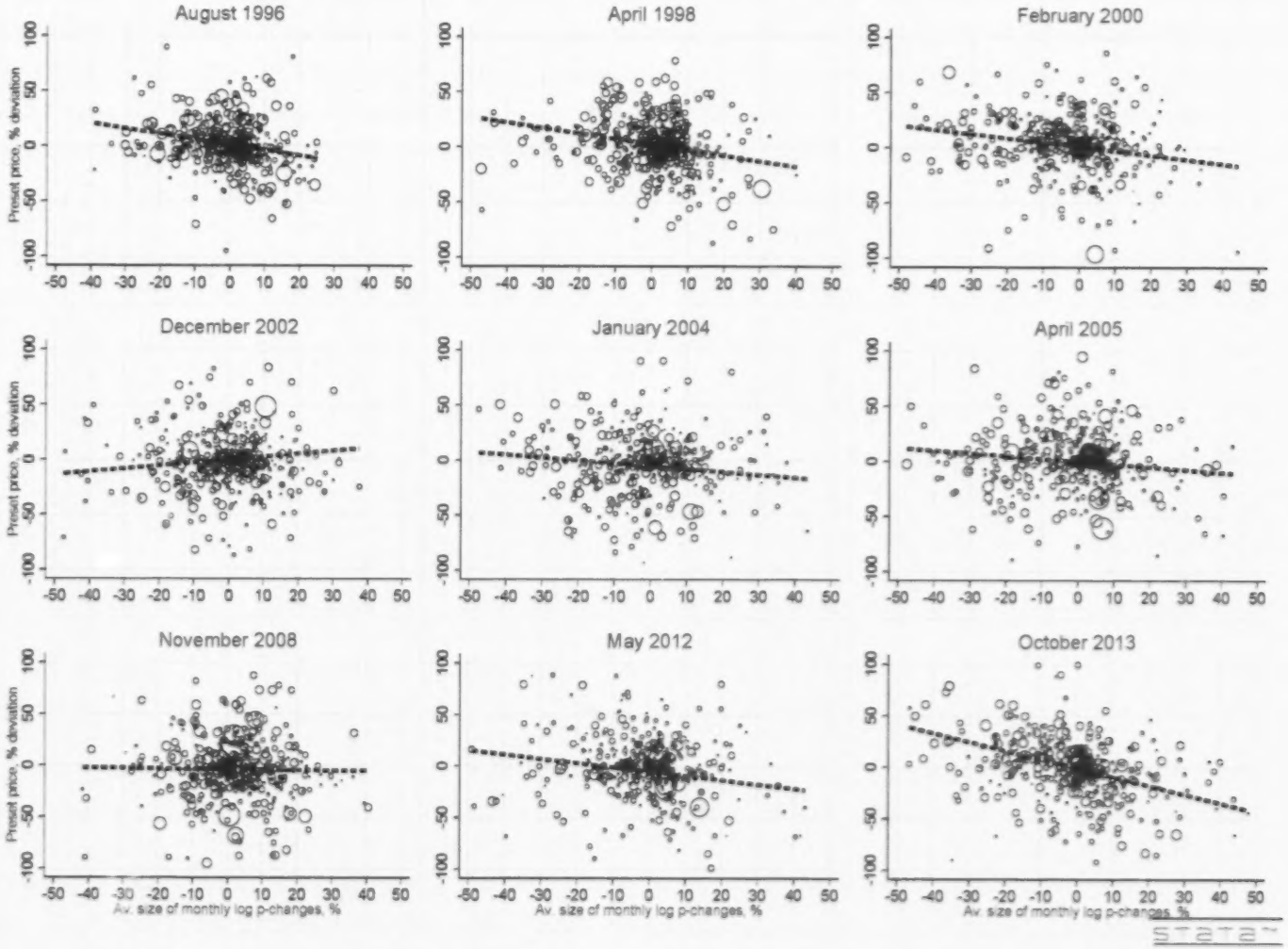
Notes: Figure provides scatter plots for largest strata in nine selected product categories in the United Kingdom, including oil, milk, hotel, and cigarettes. For each category, each point on the plot represents a monthly observation for the average size of price changes (x-axis) and preset price level (y-axis). Each plot demonstrates joint variation of P_{st}^{pre} and DP_{st} across months for a given category-stratum s. The slope of the trend line is equal to $\hat{\gamma}_s$, representing the estimated degree of price selection corresponding to the stratum.

Figure 2: Price selection across product strata, U.K. CPI data



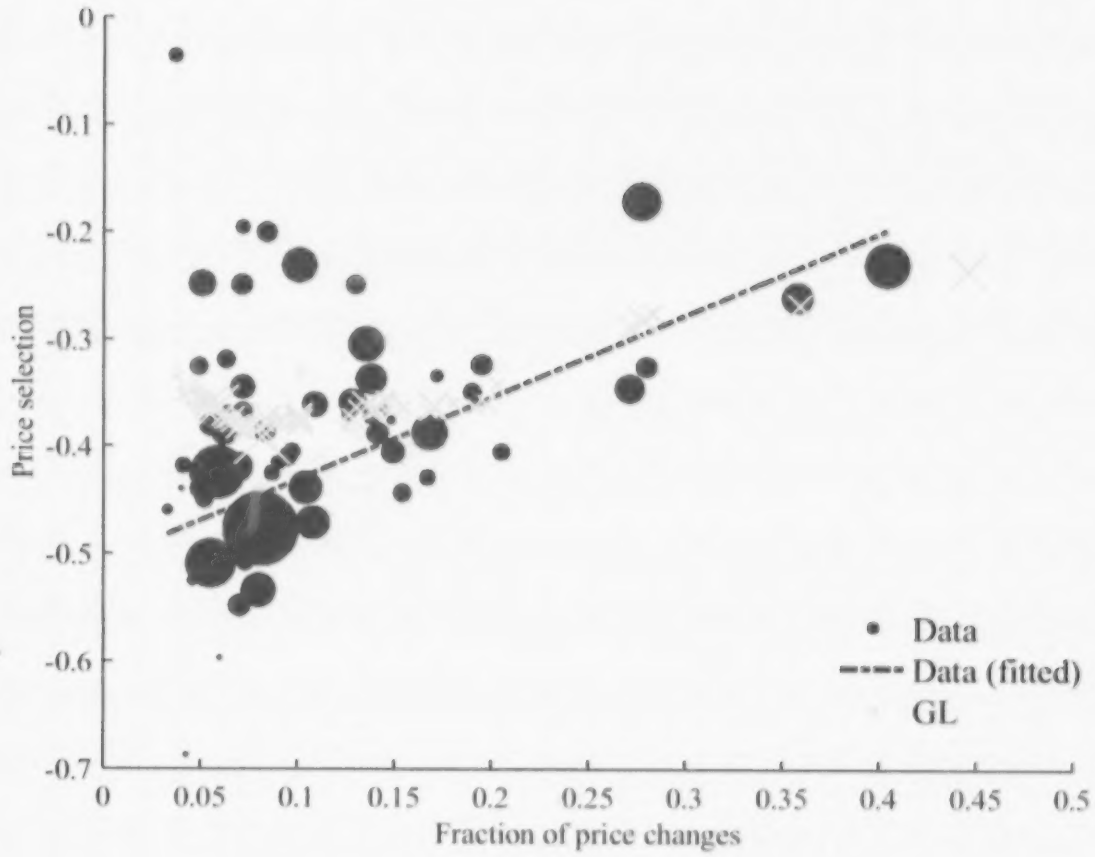
Notes: Figure shows the weighted histogram of price selection coefficients estimated for each category-stratum using regression (10), in the United Kingdom, for the case with regular prices and no substitutions, not controlling for calendar-month effects. The empty red bars show the weights for all estimated coefficients. Solid bars show the weights for coefficients that are statistically different from zero.

Figure 3: Preset price level and average size of price changes, variation over product categories for selected months, U.K. CPI data



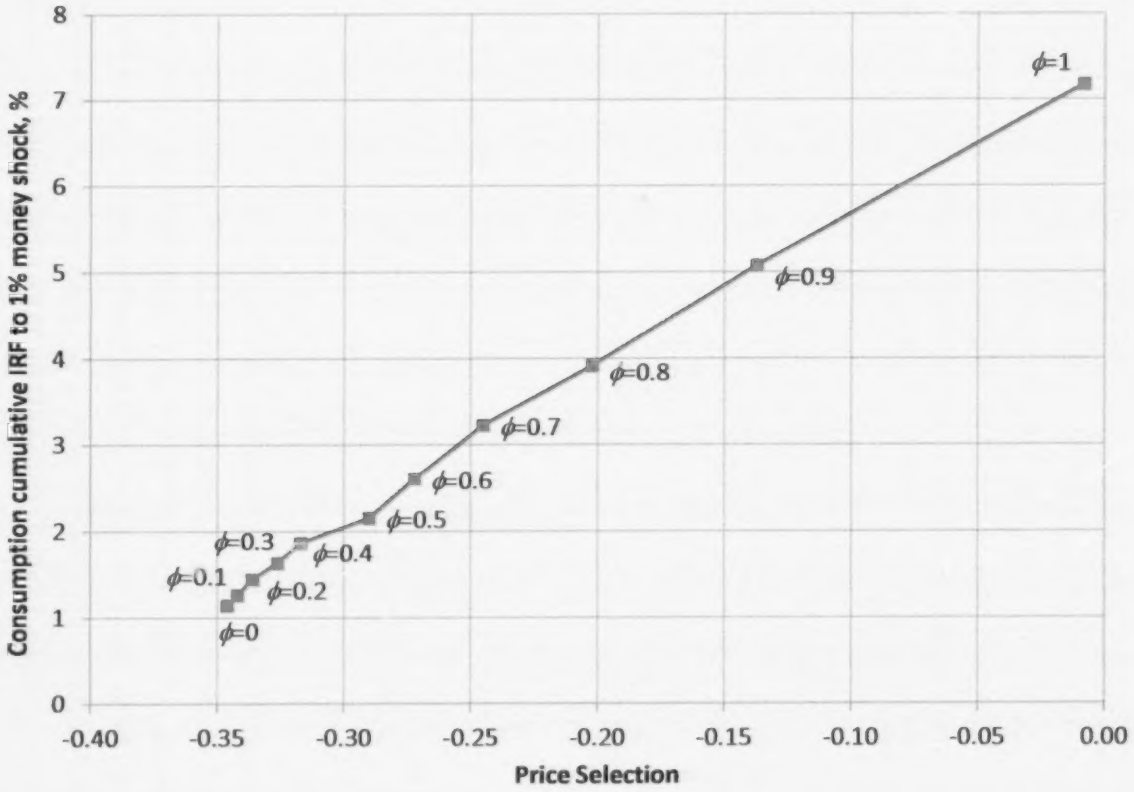
Notes: Figure provides scatter plots for nine selected months in the United Kingdom for all prices and excluding substitutions. For each month, each point on the plot represents an observation for the largest stratum in a particular category, giving the average size of price changes (x-axis) and preset price level (y-axis). The size of each point represents that stratum's consumption weight. Each plot demonstrates joint variation of P_{st}^{pre} and DP_{st} across strata in a given month. The slope of the trend line is equal to $\hat{\gamma}_s$, representing the estimated degree of price selection.

Figure 4: Sector-level price selection in sticky-price models



Notes: Scatter plot contains estimated price selection for 66 basic classes in the U.K. CPI data ("Data") and their predicted values based on weighted linear regression with a constant and basic-class-level monthly mean fraction of price changes as regressors, for the case with regular prices and no substitutions, not controlling for calendar-month effects ("Data (fitted)"). The remaining scatter points provide sector-level price selection in the 66-sector Golosov-Lucas model. In the model, we parameterize price adjustment parameters to match the frequency of price changes for each class.

Figure 5: Price selection and monetary non-neutrality in the generalized Golosov-Lucas model



Notes: Figure provides the mapping between price selection and the extent of monetary non-neutrality in the generalized Golosov-Lucas model. We vary price selection by changing the "Calvo weight" parameter ϕ, from zero (which yields the Golosov-Lucas model) to one (which delivers the Calvo model). All economies feature the same frequency of price changes. Monetary non-neutrality is measured as the consumption cumulative IRF to a 1% permanent impulse to the level of money supply.